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The rise of robots and the fall of routine jobs

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ABSTRACT

This paper examines the impact of industrial robots on jobs. We combine data on robot adoption and occupations by industry in thirty-seven countries for the period from 2005 to 2015. We exploit differences across industries in technical feasibility – defined as the industry's share of tasks replaceable by robots – to identify the impact of robot usage on employment. The data allow us to differentiate effects by the routine-intensity of employment. We find that a rise in robot adoption relates significantly to a fall in the employment share of routine manual task-intensive jobs. This relation is observed in high-income countries, but not in emerging market and transition economies.

1. Introduction

Rapid improvements in robot capabilities have fuelled concerns about the implications of robot adoption for jobs. While the creation of autonomous robots with flexible 3D movement continues to be a major challenge to engineers, rapid progress is being made. Robots can now perform a variety of tasks, such as sealing, assembling, and handling tools. As robot capabilities continue to expand and unit prices fall, firms are intensifying investment in robots (Frey and Osborne, 2017; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). What is the impact of robot adoption on labour demand? Do robots substitute for tasks previously performed by workers?

The main contribution of this paper is to empirically study the impact of industrial robots on the occupational structure of the workforce across industries in a set of high-income as well as Emerging Market and Transition Economies (EMTEs). We combine a large and detailed occupations database with data on industrial robot deliveries from the International Federation of Robotics. The database on occupational employment from Reijnders and de Vries (2018) allows us to examine the share of employment in occupations with a high content of routine tasks – i.e. tasks that can be performed by following a well-defined set of procedures. We delineate occupations along two dimensions of the characteristics of tasks performed, namely ‘analytic’ versus ‘manual’, and ‘routine’ versus ‘non-routine’.¹ We thus distinguish four key occupational group-

ings, namely routine manual, routine analytic, non-routine manual, and non-routine analytic task-intensive occupations (as in Autor et al. 2003; Reijnders and de Vries 2018; Cortes et al. 2020). We follow Graetz and Michaels (2018) in constructing measures of robot adoption by country-industry pairs and relate these to changes in occupational employment shares. Our sample covers 19 industries for 37 countries at varying levels of development from 2005 to 2015, and includes major users of industrial robots, such as the Peoples Republic of China (PRC), Japan, South Korea, Germany, and the United States. Our main finding is that country-industry pairs that saw a more rapid increase in robot adoption experienced larger reductions in the employment share of routine manual jobs.

Our approach is motivated by the following economic considerations. Firms produce a variety of products using a continuum of tasks (Acemoglu and Autor, 2011), and these products differ in the number of tasks that can be performed by robots (Graetz and Michaels, 2018). For example, the share of replaceable tasks by robots differs between apparel and automotive and appears larger in the latter.² This gives rise to differences across industries in the *technical feasibility* of robots substituting tasks previously performed by humans. Advances in machine capabilities expand the set of tasks carried out by machines (Acemoglu and Restrepo, 2018). Firms will adopt robots if it is technically feasible and the profit gains exceed the costs of purchasing and installing robots. Given higher wages in advanced countries, the technical constraints to

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¹ The distinction between manual and analytic occupations is based on differences in the extent of mental versus physical activity.

² See e.g. the Economist, 24 August 2017, “Sewing clothes still needs human hands. But for how much longer?”

robots replacing tasks are more likely to bind for firms in these countries. Hence, improvements in robot capabilities would result in a larger employment response in advanced countries compared to developing countries.

We use these economic insights in our analysis. In particular, the technical feasibility of adopting robots guides our instrumental variables (IV) strategy to identify the causal relation between robots and labour demand. Economic feasibility motivates our distinction of the impact of robot adoption between advanced and developing countries. Using two-stage least squares (2SLS) estimation, we find that robot adoption lowers the employment share of routine manual occupations. This relation is observed in high-income countries, but not in emerging market and transition economies.

This paper relates to recent studies that examine the impact of robot adoption on socio-economic outcomes. Graetz and Michaels (2018) find that robot adoption contributed to an increase in productivity growth across industries in high-income countries between 1993 and 2007. Their findings suggest that robot adoption did not reduce employment, which is corroborated in this paper. This is also observed by Dauth et al. (2019), but not by Acemoglu and Restrepo (2020), who examine geographic variation in robot adoption across the United States and find that robots are labour replacing. Dauth et al. (2019) use detailed linked employer-employee data for Germany to show that displacement effects are cancelled out by reallocation effects, such that in the aggregate no employment effects from robot adoption are observed. Data availability did not allow Graetz and Michaels (2018) to examine the impact of robots on workers that perform different tasks. Yet, Autor (2015) emphasizes that workers with routine task-intensive occupations are most likely to be affected by automation. This paper aims to contribute to our understanding of the impact of robots on such occupational shifts.

The remainder of this paper is organized as follows. Section 2 reviews the key theoretical mechanisms between automation and labour demand. Section 3 describes the methodology and instrumental variables. Section 4 documents patterns in the occupational structure of the workforce and robot adoption. Section 5 empirically studies the impact of robot adoption on the task content of labour demand. Section 6 concludes.

2. Theoretical framework

This section starts with a discussion of robot adoption in the context of a traditional capital-labour model. In this model, technology is factor-augmenting: it increases the efficiency of one of the production factors employed (Acemoglu and Autor, 2011). The model puts the focus on the complementarity and substitutability between robots and tasks performed by workers. We then describe recent modelling efforts that emphasize the ability of machines to replace workers in a widening range of tasks (Acemoglu and Restrepo, 2018). These models help to clarify mechanisms by which robots may impact labour demand and motivate our empirical analysis.

The models we describe analyse the impact of automation. Automation refers to computer-assisted machines, robotics, and artificial intelligence (Acemoglu and Restrepo, 2018). Thus, robots are a subset of automation. Robots are driven by algorithms, which have become increasingly complex. They can now operate without requiring anyone to explicitly program the mechanisms of the tasks performed. Yet, not all algorithms drive a physical machine. In fact, many algorithms are embodied in devices or applications. Once these algorithms are designed, they can be used for many tasks anywhere and at any time. For robots, the algorithms are embodied in the machines. Expanding the range of tasks performed by robots thus requires investing in robots, i.e. robots are rival (Martens and Tolan, 2018). This contrasts to algorithms, which are non-rival in nature. Robots are more frequently studied in empirical work because of the availability of statistics on their use. However,

given the properties of robotics, studies that use robot data capture only part of the impact of automation on labour.

In the traditional model, automation enhances the productivity of workers by complementing the tasks they perform (see e.g. Autor et al. 1998; Feenstra, 2008; Van Reenen 2011). Yet, for workers who perform tasks that can be substituted by automation, increasing availability of machines will lower their labour demand. Scholars have argued that new technologies tend to substitute for occupations that are intensive in routine tasks, such as assemblers, and complement non-routine task-intensive occupations, such as managers and technical scientists (Autor et al. 2003; Van Reenen 2011; Goos et al. 2014; Dauth et al. 2019). This is because for routine tasks, such as monitoring, measuring, controlling, and calculating, there are well-specified procedures which allow the task to be automated. Yet, knowing the rules that govern task procedures is not a trivial requirement. For many non-routine tasks, such as those requiring creativity and problem-solving skills, automation is difficult and rather complements the performance of these tasks done by humans. In line with this reasoning, an analysis for Western European countries by Goos et al. (2014) finds that recent technological progress has been replacing workers doing routine tasks. This is referred to as “routine-biased technological change” (RBTC).³

Predictions in the traditional model are straightforward. Firms adopt robots if it is *economically feasible* to do so, which is the case when profits exceed purchasing and installation costs. Therefore, substitution of robots for routine tasks is more likely in countries with higher wage levels, and there a fall in the fixed costs or the rental price will result in an increase in robot adoption (Graetz and Michaels, 2018).

Recent modelling efforts by Acemoglu and Restrepo (2018) add a distinctive feature of automation: the *technical ability* of machines to replace workers in a widening range of tasks. They split the production process into tasks done by workers and machines. Advances in machine capabilities expand the set of tasks carried out by machines and replace labour, thus lowering labour demand.

However, robotic automation technologies also result in the creation of new tasks that cannot be done by machines, such as programming, design, and maintenance of high-tech equipment (Acemoglu and Restrepo, 2019). This ‘re-instatement effect’ increases labour demand. The combination of tasks displaced by robots and the re-instatement of new tasks determine the reallocation of tasks between workers and machines.

Complementarity between man and machine in the Acemoglu and Restrepo (2018) model originates from two indirect effects that come on top of complementarity effects in the traditional model (Martens and Tolan, 2018). The first is a price-productivity effect whereby robot adoption lowers prices of produced goods, leading the industry to expand sales and increase its demand for labour. The second is a scale-productivity effect whereby lower aggregate goods’ prices enable the (local) economy to expand and thus also increase labour demand. The overall impact of robotization on labour demand then depends on whether the displacement or the complementary effects dominate. So far, empirical evidence on the aggregate employment effects from robotization are inconclusive.⁴

In line with Acemoglu and Restrepo (2018), Graetz and Michaels (2018) model the production process as a continuum of tasks. Yet, Graetz and Michaels (2018) assume that products differ

³ Autor et al. (2003) examine the impact of computerization on labour demand in U.S. industries from 1960–1998. They find a positive relation between the demand for non-routine tasks and computerizing industries. Ross (2017) and De La Rica et al. (2020) study the impact of RBTC on the wage premium for job tasks.

⁴ Acemoglu and Restrepo (2020) find that robot adoption lowers labour demand in US local labour markets. Dauth et al. (2019) argue in an analysis for Germany that workers displaced by robots reallocate to services and there is no decline in aggregate employment. In a cross-country analysis, Ghodsi et al. (2020) find that robot adoption does not significantly affect aggregate employment, although the impact varies at the industry level.

in the share of tasks that can be carried out by machines. Garments provide a clear example: sewing garments is a complex process that requires human intuition and dexterity, which is difficult to program. In contrast, it has proven easier to program robots to perform tasks in automobile assembly lines.⁵ Automation of car assembly lines has helped to reduce error rates and enhances the control of repeatable tasks. The technical feasibility of machines taking over tasks thus differs by industry.

In this expanded model, the improvement of machine capabilities may drive automation.⁶ That is, if robot adoption is constrained by the production nature of certain industries, the rental price of robots does not matter. Rather, it is an expansion in machine capabilities that will drive automation. Given that labour costs are higher in advanced economies, the relaxing of technological constraints by expanding robot capabilities will lead to higher economic incentives for robotization in advanced countries and hence stronger employment responses.

The traditional and expanded model capture the key economic mechanisms driving robot adoption and their employment effects. The PRC is an interesting case to illustrate how additional factors drive robot adoption. Wage levels in China are below high-income countries, but it is the world's largest adopter of industrial robots (Cheng et al. 2019). This seems counterintuitive to the modelling of robot adoption. Yet, robot use in China does coincide with rising wages and a slowdown in the growth of its working-age population. Besides labour costs, concerns over product quality and production expansion are found to influence decisions by firms in adopting robots (Cheng et al. 2019). In addition, the Chinese government has initiated various programs and provides subsidies that encourage the development of the robotics industry (Yang, 2017; Lin, 2018).

Robots may also reverse the trend to relocate fabrication activities from advanced towards low-wage countries. In an interesting contribution, Faber (2018) points out that advances in robotics will reduce production costs, no matter where the product is produced. That, he argues, will increase the attractiveness of producing domestically relative to offshoring. In effect, workers in export sectors of developing countries can be displaced by the adoption of robots, either onshore or offshore. Essentially, foreign robots act as a form of competition on the export market. Using a methodological approach similar to Acemoglu and Restrepo (2020), Faber (2018) finds that US robot adoption lowers labour demand in Mexican export-producing sectors.⁷

These models inform the empirical analysis in our paper. The next sections describe the methodology and data to examine the aggregate (cross-country) implications of robotization. We view this analysis as a complementary approach to the within-country comparisons in Acemoglu and Restrepo (2020), Dauth et al. (2019), and Faber (2018).

3. Methodology

To examine the relation between robot adoption and changes in the structure of the workforce, we estimate regressions similar to those in Graetz and Michaels (2018) that take the form

$$\Delta L_{ci} = \beta \Delta \text{Robot adoption}_{ci} + \mathbf{X}_{ci}' \gamma + \delta_c + \varepsilon_{ci}, \quad (1)$$

⁵ Clearly, some textile production can now also be nearly fully automated; an example is the Adidas 'Speed factory' (Faber, 2018). Yet, relatively speaking, the share of tasks that robots can perform varies across industries.

⁶ We thank an anonymous referee for pointing this out.

⁷ If robots result in reshoring of a factory, this will affect all workers at the exporting plant in the developing country. Faber (2018) finds that Mexican workers in commuting zones most affected by U.S. robots are low-educated machine operators and technicians in manufacturing and high-educated workers in managerial and professional occupations. Using the World Input-Output Tables, Krenz et al. (2018) find evidence for a positive relation between reshoring and the degree of automation.

where ΔL_{ci} is the change in the employment outcome of interest in industry i of country c .⁸ $\Delta \text{Robot adoption}_{ci}$ is the change of the robot stock relative to labour input in each country-industry pair.⁹ Most specifications include control variables which are changes in: investment to value added ratios, and (the natural logarithm of) value added. We also examine results controlling for the adoption of information and communication technologies (discussed below). δ_c represents country fixed effects, which in a first-difference equation are equivalent to country-specific time trends in a levels' equation. Regressions are estimated in long-run changes between 2005 and 2015 because we are interested in longer-term trends. The regressions weight industries using their 2005 employment shares within each country. This ensures that estimates reflect the importance of industries within countries, but we give equal weight to countries in the analysis (as e.g. in Graetz and Michaels, 2018). We use heteroscedasticity-robust standard errors that are two-way clustered by country and industry.¹⁰ This is a conservative approach because the resulting standard errors are typically larger compared to one-way clustering by country or industry.

3.1. Endogeneity concerns and 2SLS estimation

Estimating (1) using OLS raises several concerns about endogeneity. First, one might worry about reverse causality and omitted variable bias. For instance, industries that experience a faster growth in product demand may invest more in robots. Especially if the labour market is tight, a positive demand shock is more likely to result in investment in robots rather than an expansion of employment (Faber, 2018).¹¹ This is a case of reverse causality, because lower employment growth results in higher robot adoption. Also, relevant variables might be omitted from the regression analysis. For instance, Harrigan et al. (2016) find that adoption of new technologies is mediated by technically qualified workers. Second, one may worry about attenuation bias of β in (1) due to measurement error in the variable robot adoption. Clearly, the available data on robot adoption, discussed in Section 4.1, is imperfect, as it does not inform on the quality and other characteristics of robots installed. In addition, we estimate regression specifications in changes, which may worsen the signal-to-noise ratio compared to regressions of variables in levels. Due to measurement error, the variable robot adoption could be correlated with the error term ε_{ci} and OLS estimation of β would be biased downwards. Finally, industries that adopt robots may differ from other industries in non-random ways, which would also bias the coefficient if not appropriately controlled for. Hence, the direction of bias in β is not clear a priori, although the previous literature suggests that a downward bias in OLS is more likely (e.g. Graetz and Michaels, 2018).

In an attempt to address these endogeneity concerns, we use two industry-specific instruments introduced by Graetz and

⁸ The employment outcome of interest is either the average annual percentage growth rate in employment by country-industry pair, which is estimated as $((\ln(\text{EMP}_{ci,2015}/\text{EMP}_{ci,2005}))/10) * 100$, or it is the change in the task-specific employment share by country-industry pair, measured as the share in 2015 minus the share in 2005.

⁹ Robot adoption is defined as the number of robots installed per thousand persons employed. We follow Graetz and Michaels (2018) and use the percentile rank of the change in robot adoption as our main explanatory variable. This is further elaborated upon in Section 4.1.

¹⁰ We implement Stata's 'ivreg2' command for OLS and 2SLS regressions. Two-way clustered standard errors are robust to arbitrary heteroscedasticity and intra-group correlation within each of the two (non-nested) categories "country" and "industry" (Cameron et al. 2012). This allows for robust inference, for example, if errors are correlated within countries (e.g. due to unobserved country-specific policies) and have separate correlation structures within industries (e.g. due to technology shocks).

¹¹ In his analysis of the Mexican labour market, Faber (2018) points out that a positive demand shock due to the North American Free Trade Agreement may have put upward pressure on industries or local labour markets to adopt robots if they had less room to expand employment.

Michaels (2018) and estimate (1) using 2SLS.¹² The first instrument measures the share of each industry's labour input that is *replaceable by robots*. This instrument is constructed using information on the tasks performed by robots (IFR, 2012). As discussed above, the extent of robotization for each task could be endogenous to industry conditions. Therefore, Graetz and Michaels (2018) use information on US occupations in each industry from the 1980 census, which dates back before the rise of robots. Occupations are defined as 'replaceable' if (part of) their tasks could have been replaced by robots in 2012. They then compute the fraction of hours worked in each industry in 1980 that was performed by occupations that subsequently became more prone to replacement by robots. This instrument is not without limitations: it is based on data from the US and labour shares might therefore be different if constructed using data from other countries.¹³

The second instrument is motivated by rapid improvements in the ability of robotic arms to perform 'reaching and handling' tasks. It measures the prevalence of occupations in each industry that require *reaching and handling tasks* compared to other physical demands in 1980, prior to robot adoption. Robotic arms are a salient characteristic of robots, and much technological advances are linked to the development of these robotic arms (Graetz and Michaels, 2018). It is therefore more likely that robotic arms are a technological characteristic of robots, less driven by the demand side (due to industries' task requirements), which could reflect reverse causality. This instrument is constructed using the extent to which occupations in each US industry require reaching and handling tasks compared to other physical tasks in 1980.¹⁴ Similar limitations as to the first instrument apply here, but one may argue that this instrument is less likely to violate the exclusion restriction.

Clearly, neither instrument can guarantee to resolve all endogeneity concerns. Both instruments reflect variation across industries in the share of tasks that are potentially replaceable by robots, which may correlate with other changes over time. Nevertheless, the instruments are helpful to contrast OLS with 2SLS results.

4. Data and descriptive analysis

We first describe the data on robots and occupations in Section 4.1. Descriptive statistics are presented in Section 4.2.

4.1. Occupations and robots

We combine two datasets with information on occupations and robot purchases. The first dataset with *occupational employment* by country-industry originates from Reijnders and de Vries (2018) and was updated by Buckley et al. (2020). The data is constructed using detailed survey and census data from statistical offices for the period from 2000 to 2015. The sources used in constructing this dataset closely align with those from other studies.¹⁵ The dataset provides employment for thirteen occupational groupings by country-industry pairs. It covers 40 countries, namely the 27 members of the European Union (per January 2007), Australia, Brazil, Canada, India, Indonesia, Japan, Mexico, the PRC, Russia, South Korea, Chinese Taipei, Turkey and the United States. For each

of these countries, occupational employment shares by 35 ISIC revision 3.1 industries that cover the overall economy are distinguished. They include 14 two-digit manufacturing industries (such as textile manufacturing and electronics manufacturing), as well as agriculture, mining, construction, utilities, finance, business services, personal services, trade and transport services, and public services industries. The dataset thus has dimensions of 13 occupational groupings \times 35 industries \times 40 countries \times 16 years. Occupation data is intrinsically not exactly comparable across countries, and in practice will also vary due to differences in the type of sources and national data collection practices. Intertemporal changes within country-industries are likely more consistent because Reijnders and de Vries (2018) use data from the same national source for each country. Our empirical analysis exploits this within-country variation.

We examine the impact of robot adoption on tasks, which we distinguish into routine versus non-routine and manual versus analytic tasks. Our measurement strategy is to infer the impact of robot adoption on tasks from data on the occupational structure of the workforce. The distinction between occupations with different task intensities is based on the so-called Routine Task Intensity (RTI) index developed by Autor et al. (2003) and mapped into the International Standard Classification of Occupations (ISCO 88) by Goos et al. (2014). Table 1 provides the allocation of occupational groupings to tasks.

The second database includes deliveries of *industrial robots* by country-industry from the International Federation of Robotics (IFR).¹⁶ The IFR provides country data on the number of industrial robots delivered from 1993 onwards. Yet coverage varies and the breakdown of robot investment by country-industry is only consistently available for most countries after 2004. In addition, robot investments increased rapidly during the 2000s. We therefore build the dataset using information for all available years but focus on the period from 2005 to 2015 in the empirical analysis.¹⁷

We use the perpetual inventory method to build robot stocks, assuming a depreciation rate of 10% as in Graetz and Michaels (2018).¹⁸ We then define 'robot densification' or simply 'robot adoption' as the robot stock per thousand persons employed. We examine changes in robot adoption over time. The distribution of changes in robot adoption for the country-industries included in our analysis has mostly either zero or small positive values, with a long right tail. Analysing raw changes in robot density is therefore not recommendable and we use the percentile of changes in robot adoption (based on the employment-weighted distribution of changes) as in Graetz and Michaels (2018).¹⁹

¹⁶ Purchases of services robots are only available for recent years and few countries, which limits studying the impact on task demand of robot adoption in services sectors.

¹⁷ Program code to replicate the analysis is available from the authors upon request.

¹⁸ The perpetual inventory method to build robot stocks is: $RS_{ci,t} = (1-d) \cdot RS_{ci,t-1} + RD_{ci,t}$, where RS is the robot stock of industry i in country c at time t ; RD are robot deliveries, and d is the depreciation rate. Our main results are robust to building the robot stock using a 5 and a 15 percent depreciation rate.

¹⁹ We follow Graetz and Michaels (2018) and calculate within-country employment-weighted distributions of changes in robot adoption between 2005 and 2015. We use the Stata code that Graetz and Michaels (2018) made available at <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/5JWBXU>. Specifically, we denote robot adoption by $RA_{ci,t} = RS_{ci,t}/EMP_{ci,t}$, i.e. the robot stock per thousand persons employed in industry i of country c . We denote ws_c the weighted change in robot adoption of country c , which is the summation of changes in robot adoption by industry i weighted by their employment shares. The change in robot adoption net of the weighted change in robot adoption is $\Delta RA_{ci} = (RA_{ci,t} - RA_{ci,t-1}) - ws_c$. We then calculate the percentile rank of the change in robot adoption (ΔRA_{ci}) and use this variable in the regression analysis. The use of percentiles is common in the economics literature and helpful when the data is skewed, see for example Autor et al. (2003).

¹² The instruments are computed for 2-digit industries in the ISIC revision 3 classification, which matches with the industry information on robot stocks and occupational employment shares presented in Section 4.1. Note that the instruments do not vary across countries but only across industries.

¹³ Also note the replacement values are an upper bound because occupations are considered to be replaceable even if only part of their work can be replaced by robots.

¹⁴ Information on the task content of occupations is taken from the Dictionary of Occupational Titles.

¹⁵ For example, for the U.S., the sources are the 2000 Census and the annual American Community Surveys. These sources are also used in Autor (2015). Data for European countries are from the harmonized individual level European Union Labour Force Surveys, which are also used in Goos et al. (2014).

Table 1
Mapping occupations to tasks.

| | <i>Routine</i> | <i>Non-routine</i> |
|-----------------|---|---|
| Manual | Production workers (71-74, 81-82, 93) Agricultural workers (61-62, 92) Others (01, 999) | Support-services workers (51, 910, 912-916) Drivers (83) |
| Analytic | Administrative workers (41-42) | Legislators (11) Managers (12-13) Engineers (21, 31) Health professionals (22, 32) Teaching professionals (23, 33) Other professionals (24, 34) Sales workers (52, 911) |

Notes: Mapping of thirteen occupations from Reijnders and de Vries (2018) to four different groups based on Autor et al. (2003) and Goos et al. (2014). Numbers in brackets refer to International Standard Classification of Occupations codes (ISCO 88).

Table 2
Descriptive statistics.

| | Obs. | Mean | SD | p5 | p95 |
|--|------|-------|-------|------|------|
| <i>Dependent variables</i> | | | | | |
| Employment growth (average annual, in %) | 700 | -0.78 | 3.41 | -6.0 | 3.9 |
| Δ Routine employment share | 700 | -0.04 | 0.10 | -0.2 | 0.1 |
| Δ Routine manual employment share | 700 | -0.04 | 0.12 | -0.2 | 0.1 |
| Δ Routine analytic employment share | 700 | -0.00 | 0.05 | -0.1 | 0.1 |
| Δ Non-routine manual employment share | 700 | -0.00 | 0.06 | -0.1 | 0.1 |
| Δ Non-routine analytic employment share | 700 | 0.04 | 0.10 | -0.1 | 0.2 |
| <i>Independent variables</i> | | | | | |
| Percentile of changes in robot adoption | 700 | 0.50 | 0.29 | 0.0 | 1.0 |
| Robot adoption, 2005 | 700 | 2.23 | 10.17 | 0.0 | 10.5 |
| Robot adoption, 2015 | 700 | 4.98 | 22.54 | 0.0 | 21.1 |
| Δ Investment to value added ratio | 700 | 0.02 | 0.69 | -0.2 | 0.2 |
| Δ (natural logarithm of) value added | 700 | 0.21 | 0.60 | -0.7 | 1.1 |
| Percentile of changes in information technology adoption | 277 | 0.51 | 0.29 | 0.0 | 1.0 |
| Percentile of changes in communication technology adoption | 277 | 0.50 | 0.30 | 0.0 | 1.0 |
| IV: Reaching and handling tasks | 700 | 0.45 | 0.05 | 0.3 | 0.5 |
| IV: Replaceable tasks | 700 | 0.25 | 0.12 | 0.0 | 0.4 |

Notes: A 'Δ' in front of a variable refers to the change between 2005 and 2015. For variable descriptions, see Section 4.1. In the columns, 'obs' refers to the number of observations, SD the standard deviation, p5 the 5th percentile, and p95 the 95th percentile.

We match the data on robot adoption with occupational employment.²⁰ The nineteen sectors that are matched are 14 manufacturing industries, agriculture, mining, utilities, construction, and 'education and R&D'. The (unweighted) average employment share of these sectors in the total economy across the sampled countries is 46% and 39% in 2000 and 2015, respectively. The share varies across levels of development. It is about a quarter of the workforce in advanced countries such as Denmark, the Netherlands, and the United States throughout the sample period. It is over 50% of total persons employed in industrializers such as the PRC, Turkey, and Poland.

In most regression specifications, we control for changes in the investment to value added ratios, and (the natural logarithm of) value added.²¹ Although robots are a visible and much discussed form of

automation, computers and other digital technologies impact jobs as well. Information and Communication Technologies (ICTs) have been found to be *skill-biased*, raising the productivity of high-skilled workers and lowering demand for low-skilled workers (Feenstra 2008; Michaels et al. 2014). In contrast, robots are part of recent innovations and considered *routine-biased*, as they substitute for workers performing routine-manual tasks (Goos et al. 2014). These routine tasks are often performed by workers with a middling level of education, such as fabrication jobs involving repetitive production tasks (Autor, 2015). We therefore expect a direct effect of robot adoption on the demand for routine-manual task-intensive occupations independent of ICT investment.

To control for ICT adoption, we use data from the EU KLEMS Release 2019 for gross fixed capital formation in computing and communication equipment (Stehrer et al. 2019). These ICT investments are expressed as a share in total investment. Changes in the ICT investment share are included in the analysis, also in the form of the percentile of changes in ICT adoption (based on the employment-weighted distribution of changes).

4.2. Descriptive analysis

Table 2 shows descriptive statistics of our key dependent and explanatory variables. The top rows show changes in employment shares for occupations by task intensity. On average, the routine (manual) employment share declined by 4 percentage points between 2005 and 2015. This trend is observed in 35 out of 37 countries, but the decline in the routine share differs across countries and industries. This can be seen in Appendix Figs. 1 and 2, which depict the changes in employment shares for our four occupational groupings by country and industry, respectively. The decline in routine manual occupations is mirrored by the rise of non-routine analytic jobs, which increased by 4 percentage

²⁰ After matching the datasets, we have data for 37 countries and 19 sectors, with missing data for a few country-industry pairs. High-income countries include the 'old' EU15 countries, western offshoots, and high-income East Asian countries, namely Australia, Austria, Belgium, Canada, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Ireland, Italy, Japan, South Korea, Malta, the Netherlands, Portugal, Sweden, Chinese Taipei, and the United States. EMTes are the others, namely Brazil, the PRC, Czech Republic, Estonia, Hungary, Indonesia, India, Lithuania, Latvia, Mexico, Poland, Romania, Russia, Slovakia, Slovenia, and Turkey.

²¹ This data is obtained from the WIOD 2016 release (Timmer et al. 2015). The first control variable, investment to value added ratios may be subject to concerns about multi-collinearity as robots are part of physical capital investment. We explored the share of robot investment in overall investment by using turnover-based prices of robots for the US provided in IFR (2012). The number of robot times their unit price gives a rough approximation of nominal investment. Our estimates suggest that the share of robot investment in total investment is small, typically not exceeding 1 percent. The first differences of our data for robot adoption and investment to value added ratios are only loosely correlated, with a correlation coefficient of -0.06.

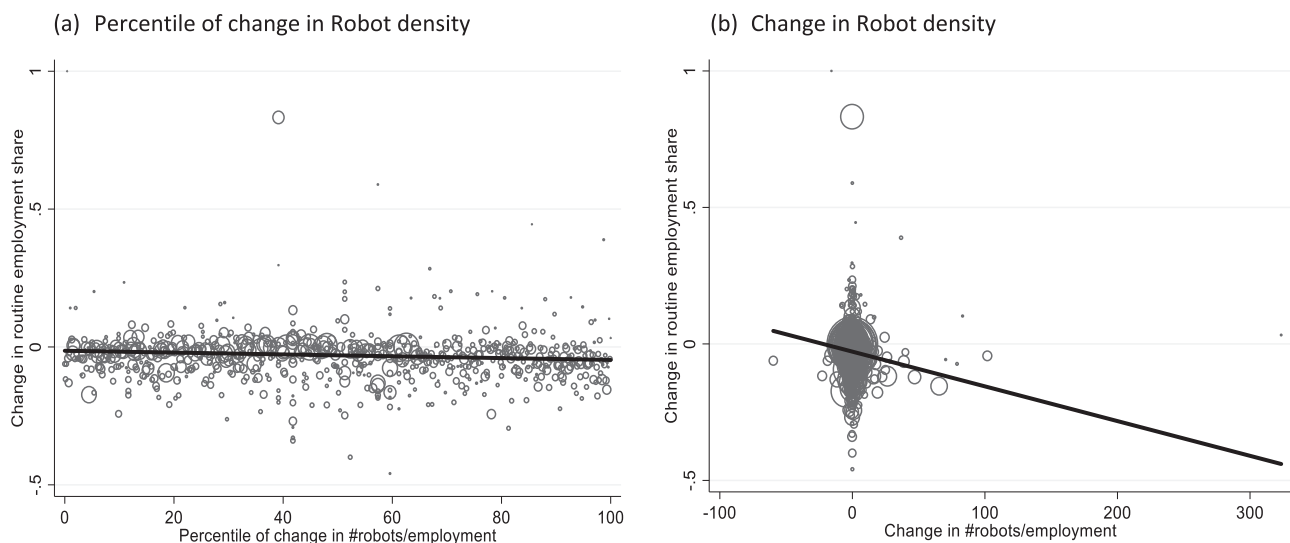


Fig. 1. Robots and the routine employment share.

Notes: Observations are country-industry cells. The size of each circle corresponds to an industry's 2005 within-country employment share. Vertical axis displays the change in the routine employment share between 2005 and 2015. Horizontal axis of panel (a) shows the percentile of changes in robot adoption (based on the employment-weighted distribution of changes), see Section 4.1. Panel (b) changes in robot adoption (based on the employment-weighted distribution of changes). Fitted regression lines are shown. Coefficients (standard errors) of the linear fit are respectively -0.00033 (0.00010) and -0.0013 (0.0004). *Sources:* see Section 4.1.

points on average.²² The comparability of the shifts in routine manual and non-routine analytic occupations across our sample of high-income countries and EMTEs makes it likely that a common set of forces contributes to shared developments in labour markets. The prime suspect is automation (Autor, 2015). At the same time, variation in country-specific experiences underscores that no common cause will explain the full diversity of labour market developments across these economies.

The average robot stock per thousand persons employed more than doubled from 2.23 in 2005 to 4.98 in 2015. The standard deviation of robotization reveals substantial variation in robotization across countries and industries. Most of this variation stems from cross-industry differences within countries as opposed to variation between countries.²³ More robots were installed in all countries, with the number of robots per thousand persons employed surging in Germany, Japan, and South Korea (see Appendix Fig. A3).²⁴ High robot density is observed in machinery, electronics, and automotive (see Appendix Fig. A4). For industries that produce chemicals and metal products we also observe an increase in robot density, albeit starting from low levels.

Appendix Fig. A5 shows the number of robots per 1,000 persons employed by industry in the PRC and Germany for 2015. This figure helps clarify the lower level of robots per thousand persons employed in China. For example, in 2015, the number of robots installed in China's automotive industry was about 50,000, which compares to a slightly lower number of around 48,500 robots in that industry for Germany. Yet, in 2015 the number of persons employed in automotive is about 6.8 million in China compared to 965 thousand in Germany, so a factor 7 difference in the size of the workforce in that industry. Hence the

number of robots installed per thousand persons employed is about 7 in China compared to 50 in Germany.

Table 2 also provides descriptive statistics for the instruments and control variables. The instruments *replaceable tasks* and *reaching and handling tasks* are positively correlated, but different.²⁵ For example, the highest share of replaceable tasks is observed in automotive and metal manufacturing, whereas the extent of reaching and handling tasks is highest in textile and food manufacturing.

Fig. 1 plots the change in the routine employment share against measures of increased robot use. In sub-figure (a), we plot the percentile of the change in robot density net of country trends on the horizontal axis, as well as the fitted regression line. The slope is negative and statistically significant. The distribution of data points around the fitted line suggest that the relationship between the routine share and the percentile of robot densification is well approximated by a linear functional form. In subfigure (b), we instead plot changes in robot density on the horizontal axis (again net of country trends), together with the fitted line. Here a linear functional form (though also negative and significant at conventional levels) seems much less adequate, and the estimated slope appears sensitive to several outlying observations near the top of the distribution of robot densification. Thus, following Graetz and Michaels (2018), in the regression analysis we will use the percentile of changes in robot densification.

Panel (a) of Fig. 2 shows a descriptive relation between robot adoption and industry average changes in the routine employment share between 2005 and 2015 (see Table A1 for the industry descriptions). We observe a (slightly) stronger reduction in the routine share for industries that invested more in robots. Sectors such as paper and utilities experienced a decline in the share of routine jobs with only a relatively small increase in robotization. In manufacturing industries such as machinery, electronics, and automotive, we observe a decrease in the share of routine jobs. These industries are also among the ones with the strongest increase in robot adoption. Panels (b) and (c) suggest both instruments are good predictors, as industries with a higher share of replaceable tasks or those more intensive in reaching and handling tasks have in-

²² Changes in the shares of routine analytic and non-routine manual jobs are typically smaller and we observe substantial variation across countries (see Appendix Fig. A1).

²³ The standard deviation of the robot stock per thousand employed between countries is 8.06 in 2015. In comparison, the standard deviation of robot adoption within countries is 21.06 in 2015. Those are calculated, respectively, as the standard deviations of country means \bar{x}_c and of their deviations $x_{ci} - \bar{x}_c + \bar{x}$, where x indicates robot adoption and \bar{x} is its global average.

²⁴ For Japan, reported deliveries and stocks of robots changed over time due to a reclassification of machines as robots (Graetz and Michaels, 2018). In Section 5.2 we show that the main results are robust to dropping Japan from the sample.

²⁵ Note the instruments are measured by industry based on data for the US (see Section 4.1) and matched to the country-industry pairs.

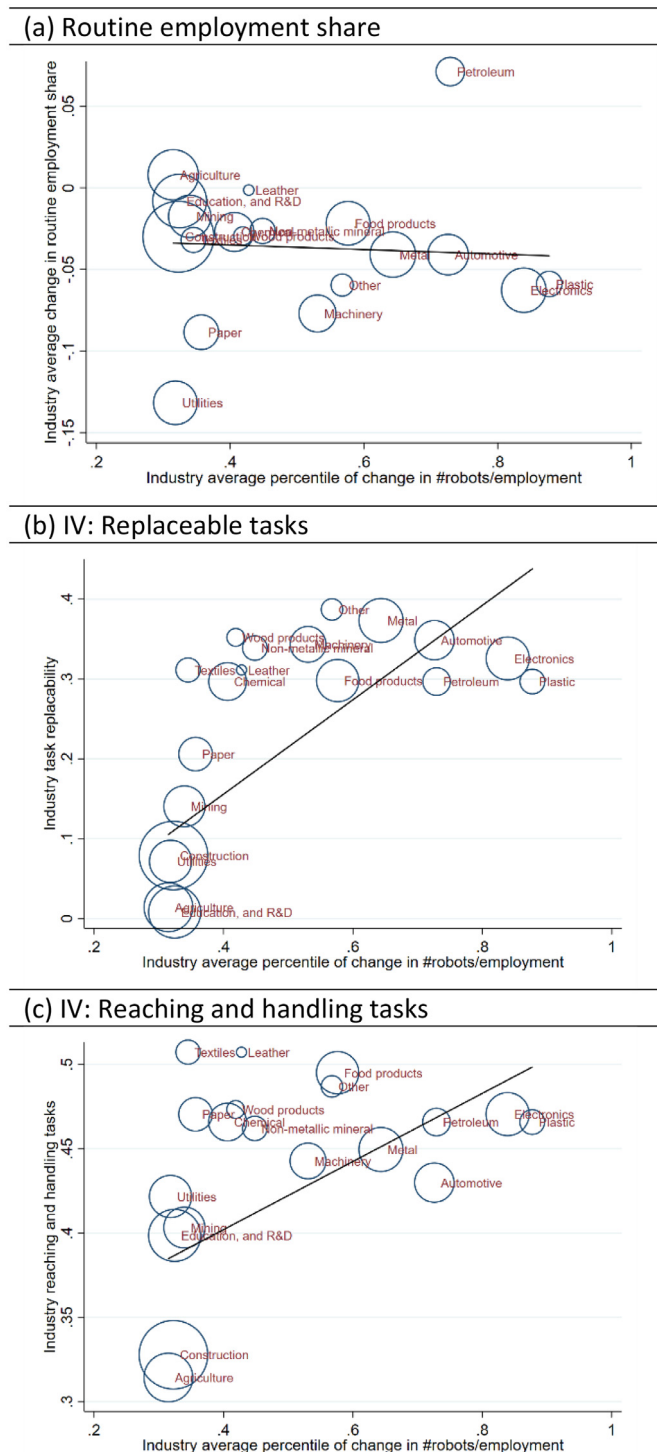


Fig. 2. Cross-industry variation in IVs and changes in the routine employment share.

Notes: On the horizontal axis is the (unweighted) average percentile of changes in robot adoption by industry. In panel (a), the vertical axis shows the industry (unweighted) average change in the routine employment share between 2005 and 2015. The coefficient (standard error) of the linear fit in panel (a) is $-0.013(0.007)$. The vertical axis of panels (b) and (c) show the values for the instruments, coefficients (standard errors) of the linear fit are respectively $0.59(0.11)$ and $0.20(0.07)$. *Sources:* see Section 4.1.

stalled more robots compared to others. The next section formally tests these relationships.

5. Econometric results

We present our main results from OLS and 2SLS regressions in Section 5.1. We find that robot adoption relates to a decline in the employment share of occupations with a high content of manual routine tasks. In Section 5.2 we present several extensions and robustness checks. We first document that results appear neither driven by specific sectors or countries nor spurious industry trends. We then exploit heterogeneity in task intensity across (blue-collar) production workers and find that robot adoption relates to declining demand for occupations that are more intensive in routine tasks. Finally, we explore whether global developments in robotization impact labour demand in EMTEs.

5.1. Main OLS and 2SLS results

Our main regression results are summarized in Table 3, with OLS results in panel A and 2SLS results in panel B. We start the analysis by regressing the average annual percentage growth of employment on robot adoption. Country fixed effects are included; thus, coefficients are identified from variation across industries. We use a conservative two-way clustering of standard errors at the country and industry level. Column 1 of Table 3 indicates that robot adoption is negatively correlated with the average growth rate of employment between 2005 and 2015. However, this relationship is not statistically different from zero. It suggests robot adoption is not labour replacing, which was also observed by Graetz and Michaels (2018). Our finding indicates this result holds in a larger country sample.

In column (2) of Table 3, we examine the relation between robot adoption and the share of routine jobs. We find that increased robot use contributes to a decline in the routine employment share. To assess the economic magnitude, consider the difference between an industry with a median trend in robot adoption and an industry with no robot adoption, which equals $0.5 \times -0.047 = -0.02$ in the OLS regression. This difference amounts to about 59% of the average change in the routine employment share (which is -0.04 , see Table 2). While this indicates a sizeable impact of robots on occupational shifts, the R-squared of 2% in column (2) where country fixed effects are partialled out, indicates that many other factors than robot adoption affect changes in the share of routine jobs. The coefficient more than doubles in the 2SLS regression, where we use the share of replaceable tasks in industries as an instrument (panel B, column 2). The instrument is positively and statistically significantly correlated with robot adoption in the first stage, which is reported in column (4) of panel B. Identification is strong, with the Cragg-Donald Wald F statistic (268.53, assuming i.i.d. errors) and the Kleibergen-Paap F-statistic (23.42) surpassing the 10% critical value (16.38). Under-identification is rejected at the 5% level of statistical significance. The considerable increase in the estimated second stage coefficient for robot adoption, when compared to OLS results, may reflect measurement error in our main explanatory variable: an increase in the noise-to-signal ratio in robot adoption will bias OLS estimates towards zero. Moreover, the increase in the coefficient in 2SLS estimates may reflect that our instrument for robot adoption only varies across industries and that global industry trends impact changes in routine employment shares (see Section 5.2 below). Using ‘reaching and handling’ tasks as an instrument gives similar results, although more prone to weak identification concerns (see Appendix Table A2).

An advantage of our dataset is the broad country coverage, including various emerging market and (post-) transition economies. In column (3) of Table 3, we differentiate the relation between robot adoption and routine shares across high-income countries and EMTEs.²⁶ We do so by

²⁶ Given the number of robots installed in the PRC, it might be less appropriate to classify it as an EMTE. To check for robustness of reported results, we omitted

Table 3
Baseline regression results of employment growth and change in routine employment share.

| Panel A: OLS | | | | |
|--|---------------------|----------------------------------|----------------------------------|--|
| | (1) Δ Employment | (2) Δ Routineemployment share | (3) Δ Routineemployment share | (4) Percentile of changes in robot adoption |
| Percentile of changes in robot adoption | -0.354 | -0.047*** | -0.055*** | |
| | (0.73) | (0.02) | (0.02) | |
| Percentile of changes in robot adoption x dummy EMTE | | | 0.040*** | |
| | | | (0.02) | |
| R ² | 0.001 | 0.025 | 0.028 | |
| Observations | 700 | 700 | 700 | |
| Number of countries | 37 | 37 | 37 | 37 |
| Panel B: 2SLS (IV: Replaceable tasks) | | | | |
| Percentile of changes in robot adoption | -2.714 | -0.120** | -0.156** | |
| | (3.03) | (0.05) | (0.06) | |
| Percentile of changes in robot adoption x dummy EMTE | | | 0.136** | |
| | | | (0.06) | |
| Replaceable tasks | | | | 0.892*** |
| | | | | (0.18) |
| Cragg-Donald Wald F statistic | | | | 268.53 |
| Kleibergen-Paap F-statistic | | | | 23.42 |
| Kleibergen-Paap under identification test (p-value) | | | | 0.013 |
| R ² | -0.052 | -0.027 | -0.053 | |
| Observations | 700 | 700 | 700 | 700 |
| Number of countries | 37 | 37 | 37 | 37 |

Notes: Robust standard errors in parentheses. Multi-way clustering by country and industry. The dependent variable employment growth in column (1) is the average annual percentage growth in employment for the period from 2005 to 2015. The dependent variable in columns (2)-(3) is the change in the routine employment share between 2005 and 2015. Column (4) reports the first stage for 2SLS estimation. The share of replaceable tasks in an industry is used as an instrument for robot adoption. Regressions include the change in the investment to value added ratio and the change in (the log of) value added between 2005 and 2015 as control variables. Country fixed effects are included in all regressions and partialled out in the reported R².

*p<0.1.

*** p<0.01

** p<0.05

interacting a dummy variable for EMTEs with robot adoption.²⁷ The relationship between robot adoption and declining routine shares appears to mainly occur in high-income countries: for both, the OLS and 2SLS regressions, the negative overall coefficient estimate for robot adoption in column (3) is almost equal in size to the positive interaction term with the EMTE dummy, indicating that the effect of robot adoption is essentially nullified in those countries.²⁸ Since technical constraints to robots replacing tasks are more likely to bind for firms in high-wage advanced countries, improvements in robot capabilities might account for the larger employment response in advanced countries compared to EMTEs.

Additionally, our dataset allows us to further disaggregate routine and non-routine employment shares into manual and analytic task-intensive occupations. Results are reported in Table 4, again with OLS results in panel A and 2SLS results in panel B.²⁹ We find that the negative relation between robot adoption and routine employment shares is exclusively driven by manual routine jobs: the estimates in column

(1) of Table 4 essentially mimic those of column (2) in Table 3, while no relationship can be found between robot adoption and analytic routine employment shares (Table 4, column 2). It thus appears robots are better suited to substitute for routine-manual tasks due to the ability of robots to manipulate objects. Conversely, the share of non-routine analytic occupations positively relates to robot adoption (column 4). This is consistent with the intuition that non-routine analytic tasks are complemented by robots in production (Autor, 2015). No relevant relationship is observed between robot adoption and changes in the manual non-routine employment share (column 3).

5.2. Robustness and extensions

We performed several robustness checks. These are summarized in Section 5.2.1. The other Sections focus on aspects considered relevant to better understand the relation between robotization and routine employment shares and to motivate future research in this area. Section 5.2.2 examines the relation between robot adoption across production occupations that differ in task intensity. Section 5.2.3 examines whether the results are driven by longer-term industry trends. Finally, Section 5.2.4 explores the role of global industry trends in robot adoption for driving country-industry changes in employment shares.

5.2.1. Robustness and heterogeneity

We first examine regression results when adding ICT investment to the analysis. This is because computers seem particularly suited to substitute for analytic tasks and the development of computer and communication equipment is not independent of robot adoption, such that omitting ICT may bias the coefficient for robot adoption. Including variables for computer and communication investment leads to a consider-

China from the sample and re-classified it as a non-EMTE. This did not alter the results (available upon request).

²⁷ In the reported 2SLS regressions, we only instrument robot adoption but not the interaction. We additionally estimated 2SLS regressions with the interaction instrumented, which required interaction of our instrument with an EMTE dummy in the first stage. Results, which are available upon request, were quantitatively and qualitatively similar to those reported, but more prone to weak identification concerns.

²⁸ OLS and 2SLS estimates of β are not statistically significantly different from zero when estimating equation (1) for EMTEs only. Results are available upon request.

²⁹ Note that first stage results for the 2SLS case are the same as in Table 3.

Table 4
Robot adoption and changes in employment shares by task type.

| Panel A: OLS | | | | |
|---|--|--|--|--|
| | (1) Δ Routinemanual employment share | (2) Δ Routineanalytic employment share | (3) Δ Non-routinemanual employment share | (4) Δ Non-routineanalytic employment share |
| Percentile of changes in robot adoption | -0.049*** (0.02) | 0.002 (0.00) | -0.008 (0.01) | 0.055*** (0.02) |
| Δ Investment to value added ratio | 0.003*** (0.00) | 0.001 (0.00) | -0.001 (0.00) | -0.003*** (0.00) |
| Δ (natural logarithm of) value added | 0.005 (0.01) | 0.002 (0.00) | 0.004 (0.00) | -0.009 (0.01) |
| R ² | 0.024 | 0.003 | 0.007 | 0.031 |
| Observations | 700 | 700 | 700 | 700 |
| Number of countries | 37 | 37 | 37 | 37 |
| Panel B: 2SLS (IV: Replaceable tasks) | | | | |
| Percentile of changes in robot adoption | -0.119** (0.05) | -0.003 (0.01) | -0.032 (0.02) | 0.152*** (0.05) |
| Δ Investment to value added ratio | 0.004*** (0.00) | 0.001 (0.00) | -0.001 (0.00) | -0.004*** (0.00) |
| Δ (natural logarithm of) value added | 0.012 (0.01) | 0.003 (0.00) | 0.006 (0.01) | -0.019** (0.01) |
| R ² | -0.020 | 0.001 | -0.021 | -0.059 |
| Observations | 700 | 700 | 700 | 700 |
| Number of countries | 37 | 37 | 37 | 37 |

Notes: Robust standard errors in parentheses. Multi-way clustering by country and industry. The dependent variable is the change in the respective employment share between 2005 and 2015. The share of replaceable tasks in an industry is used as an instrument for robot adoption. Country fixed effects are included in all regressions and partialled out in the reported R².

* $p < 0.1$.

*** $p < 0.01$

** $p < 0.05$

able decline in the sample to 277 observations because the EU KLEMS dataset does not report ICT investment by industry for many EMTEs. The estimated coefficient for the relation between robot adoption and routine employment shares is smaller but remains negative and statistically significant in the OLS and IV regressions (see column 1 of Appendix Table A3).³⁰

To avoid results being driven by certain countries, we inspect the pattern of OLS residuals (depicted in Appendix Fig. A6). Furthermore, we look at the distribution of country-specific parameter estimates, which we obtain by interacting robot adoption with a matrix of country dummy variables in our main OLS specification (see Appendix Fig. A7). There is a cluster of high fitted values for Ireland (Appendix Fig. A6, panel A) and two residuals from Romania and Sweden obtain a relatively high leverage and are potential outliers (Appendix Fig. A6, panel B). Moreover, the country-specific estimation coefficients in Appendix Fig. A7 suggest coefficient estimates for Ireland, Lithuania, and Latvia deviate from other countries. We hence exclude these 5 countries as well as Portugal, which saw somewhat different employment dynamics than the rest of our sample, according to our descriptive analysis (cf. Appendix Fig. A1). Results are reported in column (2) of Appendix Table A3. Dropping these countries does not qualitatively affect our main result.³¹

Similarly, we also compute industry-specific coefficients for the relationship between robot adoption and the share of routine jobs. Appendix Fig. A8 suggests that the electricity, gas, and water supply sector

could be an outlier that potentially drives the overall result, together with the education and R&D sector, which saw different routine employment trends according to our descriptive analysis. We thus re-estimate our baseline regressions and sequentially omit these sectors. Columns (3) and (4) of Appendix Table A3 suggest our results are not driven by these sectors, although omitting the education and R&D sector in 2SLS estimation pushes statistical significance of the robot adoption parameter slightly beyond the critical 10% level (for the null hypothesis of no relationship). To check whether countries that account for the majority of robots installed are driving our estimates, we also excluded Japan, South Korea, Germany, the PRC and the US from our estimates, leaving the baseline estimate for robotization unaffected. For the same rationale, we also excluded the high robot-adopting automotive and electronic industries (columns (5) and (6) of Appendix Table A3 respectively). All parameter estimates for robot adoption where negative and statistically different from 0 and t-tests do not allow rejecting the null hypothesis of equality of these parameter estimates with the baseline result (at the 10% level of statistical significance).

We also investigated whether a sample split at the median (0.5) of the percentile change in robot adoption affects our results. The results indicate that the parameter estimate for the slower adopters (< 0.5) are considerably higher but estimated with low precision, so that they are not statistically different from 0. Neither of the estimated OLS or IV parameters for the sample split are statistically speaking different from those in the baseline result of column (2) in table 3, in line with an approximately linear relationship suggested by panel (a) in Fig. 1.³²

³⁰ Moreover, the change in the parameter estimate appears to originate from a sample composition effect and not from omitted ICT variables: re-estimating the baseline model with the 277 observations for which ICT data is available produces the same coefficient for robot adoption as in the presence of ICT variables: -0.033***.

³¹ We also excluded several of those countries/country groups separately, with equally robust results. This also applies to excluding Japan from the analysis, which was dropped from the sample by Graetz and Michaels (2018).

³² We also examined results when clustering standard errors at the country level and not clustering at all. The alternative treatment of standard errors does not affect the statistical significance of the relation between robot adoption and the share of routine jobs in the OLS regressions and the coefficient (β) is different from zero at the 1% level of statistical significance in the 2SLS regressions.

Table 5
Robot adoption and changes in the employment share of production workers.

| Panel A: OLS | | | | | |
|---|-------------------|------------------------------------|--------------------------|-----------------------------|-------------------|
| | (1) No weight | (2) RII weight (global average) | (3) RII weight (U.S.) | (4) RII weight (Germany) | (5) RTI weight |
| Percentile of changes in robot adoption | -0.031* (0.02) | -0.066*** (0.02) | -0.065*** (0.02) | -0.058*** (0.02) | -0.103 (0.08) |
| R ² | 0.016 | 0.036 | 0.054 | 0.035 | 0.019 |
| Observations | 450 | 450 | 450 | 450 | 450 |
| Panel B: 2SLS (IV: Replaceable tasks) | | | | | |
| Percentile of changes in robot adoption | -0.083* (0.04) | -0.122** (0.06) | -0.143*** (0.05) | -0.113** (0.06) | -0.318* (0.19) |
| R ² | -0.018 | 0.013 | -0.021 | 0.006 | -0.033 |
| Observations | 450 | 450 | 450 | 450 | 450 |

Notes: Robust standard errors in parentheses. Multi-way clustering by country and industry. Dependent variable is the change in the employment share of production workers between 2005 and 2015, with weights indicated in the column header. In Panel B, the share of replaceable tasks in an industry is used as an instrument for robot adoption. Country fixed effects are included in all regressions and partialled out in the reported R².

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$.

5.2.2. Robot adoption and production workers

In Table 1, production workers are categorized as having a high content of routine-manual tasks. Yet, production workers are typically labelled blue-collar workers. Hence, the relation between robots and a declining employment share of routine manual jobs could reflect a substitution of robots for blue collar production workers, instead of a substitution for routine tasks.

It is hard to rule out such an alternative interpretation. Yet, for 24 countries in our sample we are able to distinguish seven 2-digit ISCO occupations that together comprise the occupational grouping labelled 'production workers' (cf. Table 1).³³ The routine task-intensity for each of these 2-digit occupations is provided by Autor et al. (2003) and, using an alternative approach, by Marcolin et al. (2019). We use these to create a weighted average of the change in the employment share of production workers. The weights we use are the routine intensity index (RII) from Marcolin et al. (2019) and the routine task intensity (RTI) gauged by Autor et al. (2003). The task-intensity by occupation is reported in Appendix Table A4. Clearly, the seven occupations labelled production workers are heterogeneous in the content of routine tasks.

The first column of Table 5 regresses the change in the employment share of production workers on robot adoption. Results indicate a significant negative relation between robot adoption and changes in the share of (routine manual task-intensive) production jobs. Subsequent columns examine the same relation, but here changes in the share of production jobs are calculated as a routine task-intensity weighted average change. Occupations that have a higher content of routine tasks receive a greater weight in this approach.³⁴

Weighting by routine intensity strengthens the negative association between robotization and changes in the share of production jobs: the resulting parameter estimates in columns (2)-(5) are larger compared to column (1). This result is observed if we use as weights the global average routine intensity (RII) reported by Marcolin et al. (2019), see column (2), or the RII for the US or Germany (columns (3) and (4), respectively). It is also observed if we weight occupations using the RTI

from Autor et al. (2003), see column (5), although the parameter is estimated with less statistical precision in the OLS and 2SLS regressions. Overall, these results provide additional evidence that robot adoption is related to a decline in the share of occupations that have a higher content of routine tasks.

5.2.3. Controlling for long-term industry trends

A remaining concern is that there could be a long-run decline in the share of routine tasks done by workers, which is more pronounced in industries investing more in robots yet not driven by robotization per se. A common way to examine this concern is to regress employment outcomes from a pre-period on the period during which robots were adopted.

Ideally, we thus relate pre-period employment outcomes on the current rise of robots. However, we are constrained by cross-country occupations data which are available from 2000 onwards. By 2000, robots were already being installed (Graetz and Michaels, 2018). Still, descriptive statistics in Table 2 for the number of robots per thousand persons employed in 2005 and 2015 suggest they became ubiquitous from the mid-2000s onwards.

In column (1) of Table 6 we therefore regress the change in the routine employment share between 2000 and 2005 on our post-2005 measure of robot adoption. We indeed find a relationship, although the coefficient is smaller and less precisely estimated compared to our baseline results (cf. column (2) of Table 3).³⁵ Pre-trend correlation is a necessary condition for unobserved sector heterogeneity, but it is not a sufficient condition to render identification invalid. This is partly because the pre-trend does not pre-date the rise of robots. Yet, to control for longer-term industry trends, we provide two additional estimation approaches: explicitly accounting for pre-trends by including the change in the routine employment share between 2000 and 2005 as a lagged dependent variable and including industry fixed effects.

Columns (2) and (3) of Table 6 add pre-trends to the regressions on changes in the routine employment share and the routine manual employment share, respectively (cf. column (2) of Table 3 and column (1) of Table 4). We observe a positive autocorrelation in employment dynamics. Yet, robot adoption adds additional information beyond those pre-trends as the coefficient remains statistically significant. The esti-

³³ The seven ISCO 2-digit occupations that can be distinguished are ISCO 88 codes 71, 72, 73, 74, 81, 82, and 93. The countries for which we are able to make this split are Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, Latvia, Malta, the Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Turkey, and the United Kingdom.

³⁴ The task-intensity measures are Pearson-transformed, i.e. centred at 0 with a standard deviation of 1. We added +1 to the measure. Hence, an occupation with mean routine intensity gets a weight of 1, a below-average routine intensity occupation a lower weight, and an above-average routine intensity occupation a weight above 1 (see Appendix Table A4).

³⁵ Note that the pre-trends in employment share changes cover a 5 year period. Estimated coefficients and standard errors thus have to be approximately multiplied by a factor 2 to make them comparable with our main results for the 10 year period from 2005 to 2015. When the pre-trends are included as lagged dependent variables (columns 2 and 3 of Table 6), they accordingly have to be divided by 2.

Table 6
Accounting for long-term industry trends.

| Panel A: OLS | | | | | |
|--|---|---|--|---|--|
| | (1) Δ Routine employment share 2000-2005 | (2) Δ Routine employment share | (3) Δ Routine manual employment share | (4) Δ Routine employment share | (5) Δ Routine manual employment share |
| Percentile of changes in robot adoption | -0.020** (0.01) | -0.044*** (0.01) | -0.046*** (0.01) | -0.016*** (0.00) | -0.026*** (0.01) |
| Change in dependent variable, 2000-2005 | | 0.174* (0.10) | 0.147* (0.08) | | |
| Industry Fixed Effects | No | No | No | Yes | Yes |
| R ² | 0.014 | 0.035 | 0.030 | 0.007 | 0.007 |
| Observations | 700 | 700 | 700 | 700 | 700 |
| Panel B: 2SLS (IV: Replaceable tasks) | | | | | |
| Percentile of changes in robot adoption | -0.053** (0.02) | -0.113** (0.05) | -0.114** (0.05) | | |
| Change in dependent variable, 2000-2005 | | 0.133 (0.09) | 0.109 (0.08) | | |
| Industry Fixed Effects | No | No | No | | |
| R ² | -0.018 | -0.012 | -0.010 | | |
| Observations | 700 | 700 | 700 | | |

Notes: Robust standard errors in parentheses. Multi-way clustering by country and industry. The dependent variable is the change in the respective employment share over the respective period. The share of replaceable tasks in an industry is used as an instrument for robot adoption. Regressions include the change in the investment to value added ratio and the change in (the log of) value added between 2005 and 2015 as control variables. Country fixed effects are included in all regressions and partialled out in the reported R².

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$.

mated coefficient is comparable to the baseline results. Perhaps the most convincing evidence that the negative relationship between routine employment shares and robot adoption is not exclusively driven by spurious industry dynamics can be found in columns (4) and (5) of Table 6, where we add industry fixed effects to our OLS regressions.³⁶ This is a restrictive model that assumes industry-specific time trends in levels and thus not only accounts for heterogeneous industry employment trends but also removes a considerable degree of variation in the data that may be relevant for identification. Yet, the negative association between robotization and routine employment trends is still observed and statistically significant.

5.2.4. Global developments in robot adoption

As discussed in Section 2, advances in the technical ability of robots might relate to the “reshoring” of jobs to advanced countries. For example, Faber (2018) observes a decrease in labour demand in Mexico associated with robot adoption in the United States. We explore this relation in a cross-country context using two measures of robot adoption that vary across industries but not across countries. First, we take global averages, defined as the cross-country mean of the percentile change in robot adoption by industry. This reflects the idea that in an interconnected world those industries with higher robot adoption will see faster declines in routine employment shares regardless of the location of production. Second, we use robot adoption of U.S. industries to represent global industry trends.

Results are reported in Table 7. In columns (1) and (2) the global averages of industry-specific robot adoption is used. The regressions suggest a statistically significant and negative relation between changes in the routine employment share and global trends in robot adoption.³⁷ Interestingly, the positive interaction between robot adoption and EMTEs

shown in column (2) no longer makes up for the negative overall robot adoption parameter: the hypothesis that the sum of both parameters adds up to 0 can be rejected at the 5% level of statistical significance. This suggests that global developments in robot adoption impact labour markets in EMTEs. Note, however, this is not observed if we use robot adoption in U.S. industries to characterize global trends (see column (4)).³⁸ Nevertheless, these exploratory regressions provide suggestive evidence for the potential relevance of global production networks and associated job reshoring patterns due to automation, which remains an interesting area for further research.

6. Concluding remarks

We study the relation between industrial robots and occupational shifts by task content. Using a panel of 19 industries in 37 high-income and EMTEs from 2005-2015, we find that increased use of robots is associated with positive changes in the employment share of non-routine analytic jobs and negative changes in the share of routine manual jobs. The patterns that we document are robust to instrumental variable estimation and the inclusion of various control variables, but they differ across levels of economic development: we observe a significant relation for high-income countries, but not in EMTEs. Finally, we do not find a significant relation between industrial robot adoption and aggregate employment growth. This suggests that industrial robots did not replace jobs, but they did impact task demand and thus had disruptive effects on employment.

Our analysis covered industrial robots, but much of the recent robotic developments have been taking place in services, such as the emergence of medical robots, logistics handling robots, and delivery by

³⁶ We cannot estimate the model with industry fixed effects using 2SLS because the instrument only varies across industries.

³⁷ Using measures of robot adoption that vary across industries but not across countries, we also do not find a statistical significant association between robot

adoption and the average annual percentage growth in employment in specifications with and without the interaction with a dummy for EMTEs.

³⁸ It is also not observed if we use robot adoption in German industries to characterize global trends.

Table 7
Global industry trends in robot adoption.

| Panel A: OLS | | | | |
|--|---|---|---|---|
| Robot measure: | (1) Global average Δ Routineemployment share | (2) Global average Δ Routineemployment share | (3) U.S. Δ Routineemployment share | (4) U.S. Δ Routineemployment share |
| Alternative measure robot adoption | -0.084*** (0.03) | -0.101*** (0.04) | -0.045*** (0.01) | -0.052*** (0.02) |
| Alternative measure robot adoption x dummy EMTE | | 0.054*** (0.02) | | 0.052*** (0.02) |
| R ² | 0.034 | 0.039 | 0.039 | 0.043 |
| Observations | 700 | 700 | 700 | 700 |
| Panel B: 2SLS (IV: Replaceable tasks) | | | | |
| Alternative measure robot adoption | -0.128*** (0.05) | -0.152*** (0.06) | -0.067*** (0.02) | -0.080*** (0.03) |
| Alternative measure robot adoption x dummy EMTE | | 0.089** (0.04) | | 0.086** (0.03) |
| R ² | 0.026 | 0.030 | 0.030 | 0.033 |
| Observations | 700 | 700 | 700 | 700 |

Notes: Robust standard errors in parentheses. Multi-way clustering by country and industry. The dependent variable is the change in the routine employment share between 2005 and 2015. Column headers indicate which type of global measure has been used to calculate industry-specific robot adoption. The share of replaceable tasks in an industry is used as an instrument for robot adoption. Regressions include the change in the investment to value added ratio and the change in (the log of) value added between 2005 and 2015 as control variables. Country fixed effects are included in all regressions and partialled out in the reported R². *p<0.1.

*** p<0.01

** p<0.05

means of drones. It is therefore likely that robots will continue to disrupt labour markets and result in reallocation dynamics. Studying and understanding the socio-economic consequences of these disruptions will be important (see e.g. Dauth et al. 2019). Retraining and reskilling of workers seems inevitable, which should spur a major rethinking about educational goals, lifelong learning, and developing the right skills (Kim and Park, 2020).

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Appendix

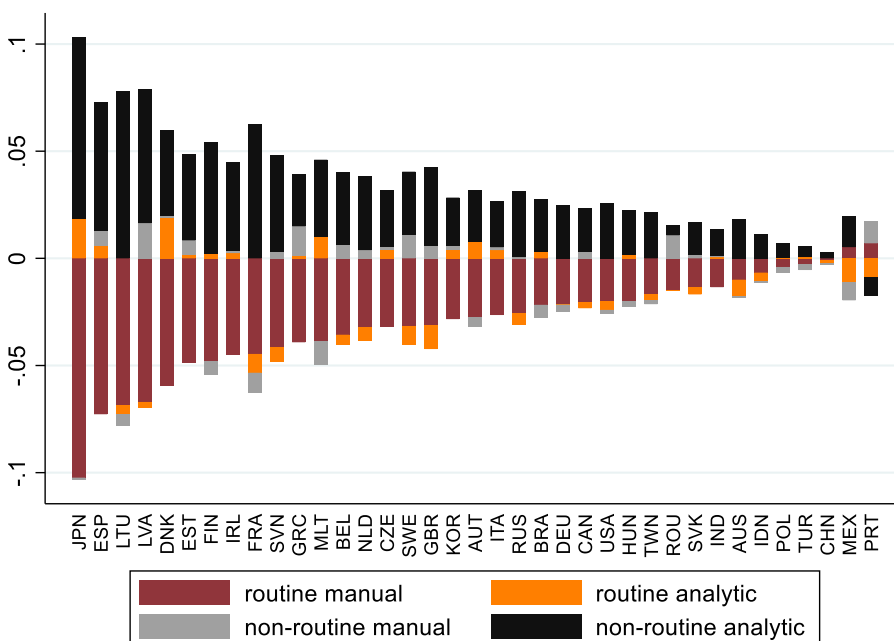


Fig. A1. Changes in employment shares by country and task type between 2005 and 2015.

Notes: change in employment shares between 2005 and 2015. For aggregation, industries included in the sample are weighted using their 2005 employment share within the sample for each country. Agriculture is omitted in the calculation for Ireland, which reports a sudden swing in the routine manual employment share (see Section 5.2.1 for robustness check excluding Ireland). Source: updated occupations database from Reijnders and de Vries (2018) by Buckley et al. (2020).

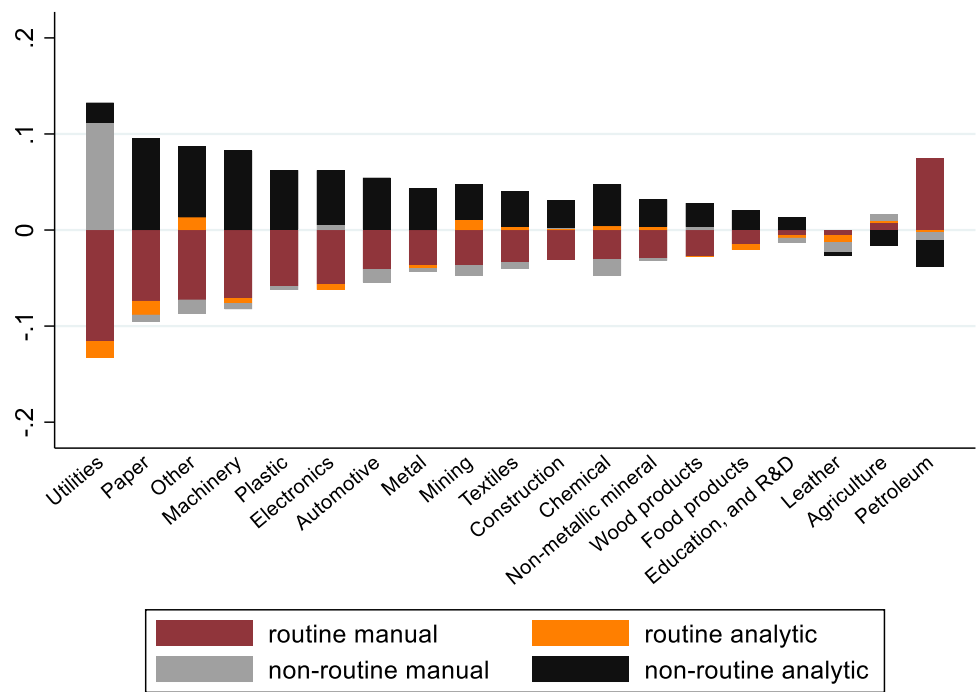


Fig. A2. Changes in employment shares by industry and task type between 2005 and 2015. *Notes:* change in employment shares by industry between 2005 and 2015. Unweighted average changes. Source: updated occupations database from [Reijnders and de Vries \(2018\)](#) by [Buckley et al. \(2020\)](#).

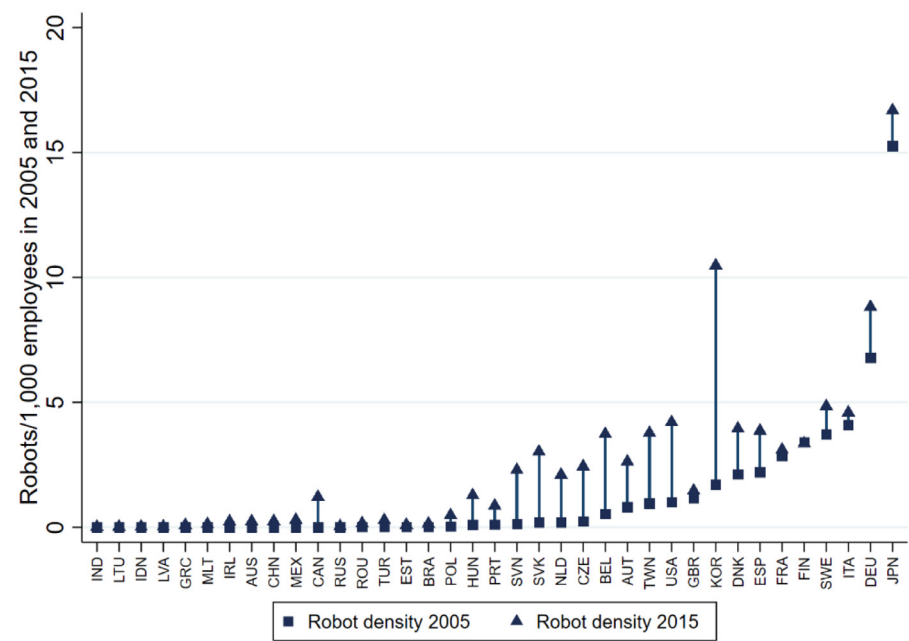


Fig. A3. Robotization by country in 2005 and 2015. *Notes:* robot stock per thousand employees by country in 2005 (squares) and 2015 (triangles). Sources: robot stock from IFR and employment from [Reijnders and de Vries \(2018\)](#) updated by [Buckley et al. \(2020\)](#).

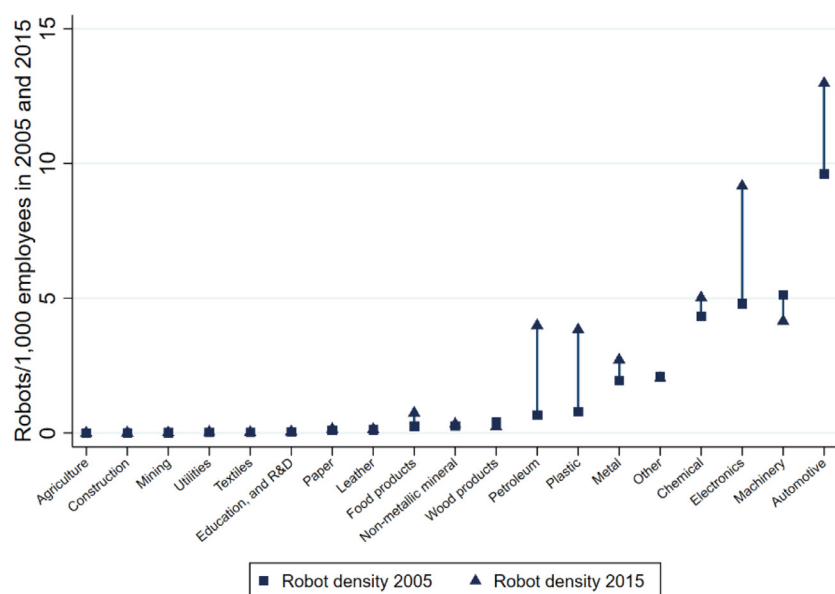


Fig. A4. Robotization by industry in 2005 and 2015.

Notes: robot stock per thousand persons employed by industry in 2005 (squares) and 2015 (triangles). Sources: robot stock from IFR and employment from [Reijnders and de Vries \(2018\)](#) updated by [Buckley et al. \(2020\)](#).

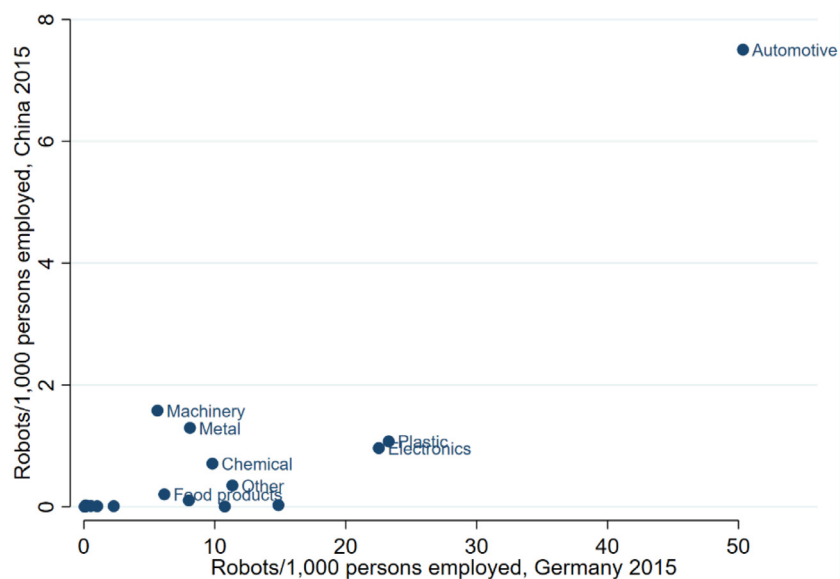


Fig. A5. Robotization by industry in the PRC and Germany, 2015.

Notes: robot stock per thousand persons employed by industry. Sources: robot stock from IFR and employment from [Reijnders and de Vries \(2018\)](#) updated by [Buckley et al. \(2020\)](#).

Table A1
Industry codes.

| ISIC rev 3.1 code | Short description | Long description |
|-------------------|----------------------|--|
| AtB | Agriculture | Agriculture, hunting, forestry and fishing |
| 15t16 | Food products | Food, beverages and tobacco |
| 17t18 | Textiles | Textiles and textile |
| 19 | Leather | Leather, leather and footwear |
| 20 | Wood products | Wood and products of wood and cork |
| 21t22 | Paper | Pulp, paper, printing and publishing |
| 23 | Petroleum | Coke, refined petroleum and nuclear fuel |
| 24 | Chemical | Chemicals and chemical |
| 25 | Plastic | Rubber and plastics |
| 26 | Non-metallic mineral | Other non-metallic mineral |
| 27t28 | Metal | Basic metals and fabricated metal |
| 29 | Machinery | Machinery, not elsewhere classified (n.e.c.) |
| 30t33 | Electronics | Electrical and optical equipment |
| 34t35 | Automotive | Transport equipment |
| 36t37 | Other | Manufacturing n.e.c.; recycling |
| C | Mining | Mining and quarrying |
| E | Utilities | Electricity, gas and water supply |
| F | Construction | Construction |
| M | Education, and R&D | Education, and R&D |

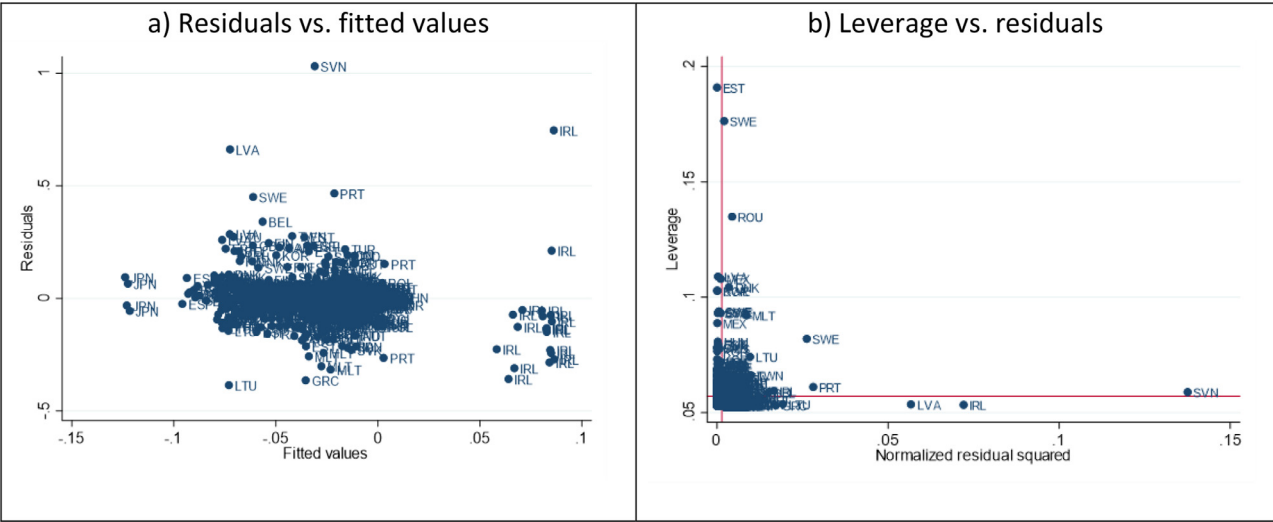


Fig. A6. Residual patterns for main OLS specification.
Notes: Panel a plots the OLS residuals (deviation of predicted from actual value, vertical axis) against the fitted values from the OLS model (horizontal axis). Panel b plots the leverage (influence) every observation gets in the OLS regression, a measure of distance from the mean in the explanatory variables (vertical axis), against normalized squared residuals (horizontal axis). All values are based on column (2) in panel A of Table 3.

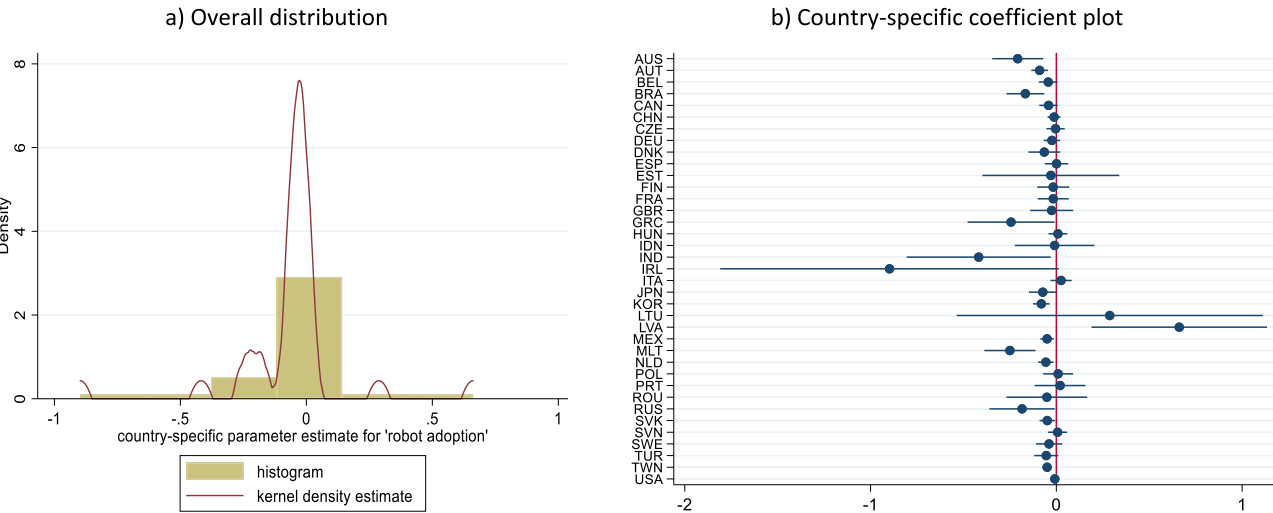
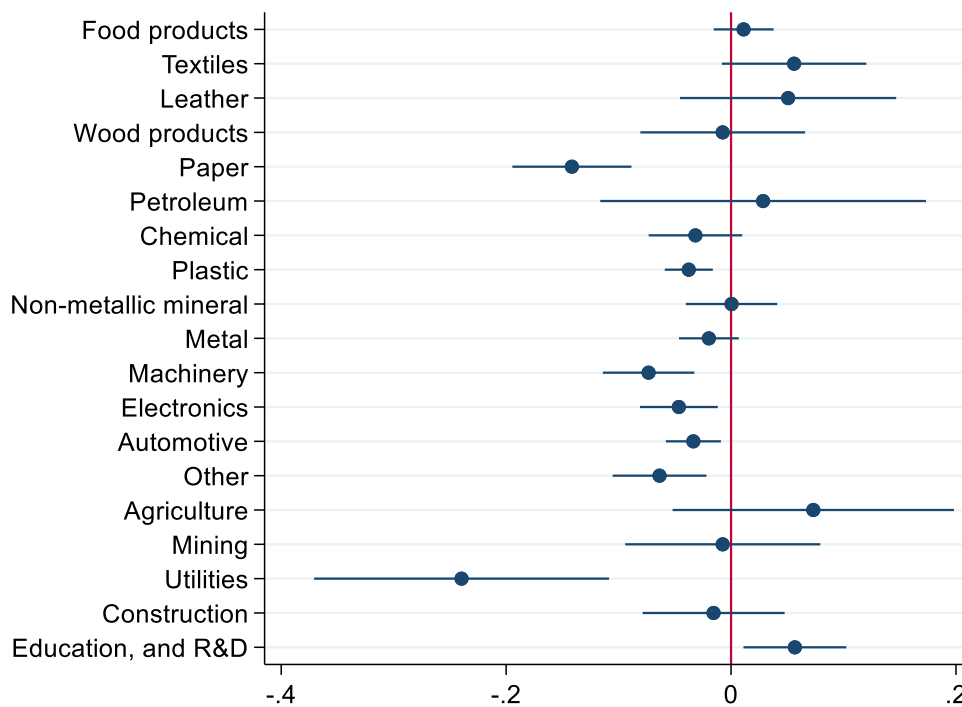


Fig. A7. Country-specific OLS coefficients.
Notes: Fig 6 displays country-specific coefficients for an OLS regression model where we augment the specification in column (2) of Table 3 (panel A) with an interaction of robot adoption with country dummy variables. The distribution of those country-specific interactions with robot adoption is depicted in Figure 6(a) using a histogram and a kernel density estimator. Figure 6(b) displays the estimated coefficients by country, including their 95% confidence interval.

**Fig. A8.** Industry-specific OLS coefficients.

Notes: Figure displays industry-specific coefficients for a regression model where we augment the specification in column (2) of Table 3 (panel A) with an interaction of robot adoption with industry dummy variables. The estimated coefficients by industry are depicted together with their 95% confidence interval.

Table A2
2SLS results for reaching and handling.

| | (1) Δ Employment | (2) Δ Routineemployment share | (3) Δ Routineemployment share | (4) Percentile of changes in robot adoption |
|--|---------------------|-------------------------------------|-------------------------------------|---|
| Percentile of changes in robot adoption | -1.586 (3.81) | -0.134* (0.08) | -0.169 (0.11) | |
| Percentile of changes in robot adoption x dummy EMTE | | | 0.149 (0.10) | |
| Reaching and handling tasks | | | | 1.438*** (0.43) |
| Cragg-Donald Wald F statistic | | | | 129.47 |
| Kleibergen-Paap F-statistic | | | | 11.44 |
| Kleibergen-Paap under identification test (p-value) | | | | 0.025 |
| R ² | -0.013 | -0.047 | -0.075 | |
| Observations | 700 | 700 | 700 | 700 |
| Number of countries | 37 | 37 | 37 | 37 |

Notes: Robust standard errors in parentheses. Multi-way clustering by country and industry. The dependent variable employment growth in column (1) is the average annual growth in employment for the period from 2005 to 2015. The dependent variable in columns (2)-(3) is the change in the routine employment share between 2005 and 2015. Column (4) reports the first stage for 2SLS estimation. Reaching and handling tasks are used as an instrument for robot adoption. Regressions include the change in the investment to value added ratio and the change in (the log of) value added between 2005 and 2015 as control variables. Country fixed effects are included in all regressions and partialled out in the reported R².

***p<0.01.

**p<0.05.

*p<0.1.

Table A3
Robustness analysis.

| Panel A: OLS | | | | | | | | |
|---------------------------------------|-------------------------|---------------------|----------------------------|------------------------------------|--|--|--|--|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | ICT investment included | 6 countries omitted | Sector 'utilities' omitted | Sector 'education and R&D' omitted | Excluding several major robot-adopting countries | Excluding several high-adopting industries | Percentile of changes in robot adoption <0.5 | Percentile of changes in robot adoption >0.5 |
| Perc. of Δ robot adoption | -0.033** (0.01) | -0.039*** (0.01) | -0.052*** (0.01) | -0.040** (0.02) | -0.047*** (0.02) | -0.038** (0.02) | -0.158 (0.10) | -0.066* (0.04) |
| Perc. of Δ IT adoption | 0.024 (0.03) | | | | | | | |
| Perc. of Δ CT adoption | -0.009 (0.03) | | | | | | | |
| R ² | 0.044 | 0.044 | 0.032 | 0.019 | 0.021 | 0.012 | 0.011 | 0.029 |
| Observations | 277 | 588 | 663 | 663 | 605 | 626 | 349 | 351 |
| Panel B: 2SLS (IV: Replaceable tasks) | | | | | | | | |
| Perc. of Δ robot adoption | -0.085** (0.04) | -0.109*** (0.04) | -0.134*** (0.05) | -0.106 (0.07) | -0.130** (0.05) | -0.135** (0.06) | -1.367 (0.84) | -0.060 (0.21) |
| Perc. of Δ IT adoption | 0.035* (0.02) | | | | | | | |
| Perc. of Δ CT adoption | -0.021 (0.03) | | | | | | | |
| R ² | -0.015 | -0.065 | -0.038 | -0.022 | -0.032 | -0.052 | -0.448 | 0.029 |
| Observations | 277 | 588 | 663 | 663 | 605 | 626 | 349 | 351 |

Notes: See Section 5.2.1. Regressions for the percentile of changes in robot adoption (Perc. of Δ robot adoption) on changes in the routine employment share between 2005 and 2015. Robust standard errors in parentheses. Multi-way clustering by country and industry. In column (1) the percentile of changes in information technology adoption (Perc. of Δ IT adoption) and the percentile of changes in communication technology adoption (Perc. of Δ CT adoption) are included as explanatory variables. Panel B uses the share of replaceable tasks in an industry as an instrument for robot adoption. Regressions include the change in the investment to value added ratio and the change in (the log of) value added between 2005 and 2015 as control variables. Country fixed effects are included in all regressions and partialled out in the reported R².

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

Table A4
Routine task-intensity of occupations grouped as 'production workers'.

| ISCO88 code | Description occupation | RII (Global average) | RII (U.S.) | RII (Germany) | RTI |
|-------------|---|----------------------|------------|---------------|-------|
| 71 | Extraction and building trades workers | 1.031 | 1.209 | 0.955 | 0.815 |
| 72 | Metal, machinery and related trade work | 1.269 | 1.209 | 0.955 | 1.457 |
| 73 | Precision, handicraft, craft printing and related trade workers | 0.952 | 1.598 | 0.477 | 2.589 |
| 74 | Other craft and related trade workers | 0.810 | 0.626 | 0.477 | 2.238 |
| 81 | Stationary plant and related operators | 2.930 | 2.181 | 3.342 | 1.323 |
| 82 | Machine operators and assemblers | 2.480 | 3.541 | 2.865 | 1.493 |
| 93 | Labourers in mining, construction, manufacturing and transport | 2.886 | 2.375 | 3.342 | 1.449 |

Notes: The routine intensity index (RII) is from Marcolin et al. (2019) and the routine task intensity (RTI) from Autor et al. (2003). The measures are Pearson-transformed, i.e. centred at 0 with a standard deviation of 1. We added +1 to the measure. Hence, an occupation with mean routine intensity gets a weight of 1, a below-average routine intensity occupation a lower weight, and an above-average routine intensity occupation a weight above 1.

References

- Acemoglu, D., Autor, D., 2011. Skills, tasks and technologies: implications for employment and earnings. In: *Handbook of Labour Economics*, vol. 4, pp. 1043–1171 Elsevier.
- Acemoglu, D., Restrepo, P., 2018. Modeling automation. *Am. Econ. Rev. Pap. Proc.* 108, 48–53.
- Acemoglu, D., Restrepo, P., 2019. Automation and new tasks: how technology displaces and reinstates labor. *J. Econ. Perspect.* 33 (2), 3–30.
- Acemoglu, D., Restrepo, P., 2020. Robots and jobs: evidence from US local labor markets. *J. Polit. Econ.* forthcoming.
- Autor, D.H., Katz, L.F., Krueger, A.B., 1998. Computing inequality: have computers changed the labor market? *Quart. J. Econ.* 113 (4), 1169–1213.
- Autor, D.H., Levy, F., Murnane, R.J., 2003. The skill content of recent technological change: an empirical exploration. *Quart. J. Econ.* 118 (4), 1279–1333.
- Autor, D., 2015. Why are there still so many jobs? The history and future of workplace automation. *J. Econ. Perspect.* 29 (3), 3–30.
- Buckley, P.J., Strange, R., Timmer, M.P., de Vries, G.J., 2020. Catching-up in the global factory: analysis and policy implications. *J. Int. Bus. Policy* 3 (2), 79–106.
- Cameron, A.C., Gelbach, J.B., Miller, D.L., 2012. Robust inference with multi-way clustering. *J. Bus. Econ. Stat.* 29 (2), 238–249.
- Cheng, H., Jia, R., Li, D., Li, H., 2019. The rise of robots in China. *J. Econ. Perspect.* 33 (2), 71–88.
- Cortes, G.M., Nekarda, C.J., Jaimovich, N., Siu, H.E., 2020. The dynamics of disappearing routine jobs: a flows approach. *Labour Econ.* 65.
- Dauth, W., Findeisen, S., Suedekum, J., Woessner, N., 2019. The Adjustment of Labor Markets to Robots. Mimeo University of Würzburg.
- De La Rica, S., Gortazar, L., Lewandowski, P., 2020. Job Tasks and Wages in Developed Countries: Evidence from PIAAC. *Labour Econ.* 65.
- Faber, M., 2018. Robots and Reshoring: Evidence from Mexican Local Labor Markets WWZ Working Paper 2018/27.
- Feenstra, R.C., 2008. Offshoring in the global economy. *Ohlin Lect.*
- Frey, C., Osborne, M., 2017. The future of employment: how susceptible are jobs to computerisation? *Technol. Forecast. Soc. Change* 114, 254–280.
- Ghods, M., Reiter, O., Stehrer, R., Stöckinger, R., 2020. Robotisation, Employment and Industrial Growth Intertwined Across Global Value Chains WIIW Working Paper No. 177.
- Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: routine-biased technological change and offshoring. *Am. Econ. Rev.* 104 (8), 2509–2526.
- Graetz, G., Michaels, G., 2018. Robots at work. *Rev. Econ. Stat.* 100 (5), 753–768.
- Harrigan, J., Reshef, A., Toubal, F., 2016. The March of the Techies: Technology, Trade, and Job Polarization in France, 1994–2007 National Bureau of Economic Research No. 22110.
- International Federation of Robotics, 2012. World Robotics Industrial Robots 2012 Report.
- Kim, J., Park, C.Y., 2020. Education, Skill Training, and Lifelong Learning in the Era of Technological Revolution. ADB Economics working paper series No. 606.
- Krenz, A., Prettnner, K., Strulik, H., 2018. Robots, Reshoring, and the Lot of Low-Skilled Workers CEPR Working Paper No. 351.
- Lin, O., 2018. Chinese Robotic Firms Thrive, Thanks to Subsidies. *Asia Times* May 8.
- Marcolin, L., Miroudot, S., Squicciarini, M., 2019. To be (routine) or not to be (routine), that is the question: a cross-country task-based answer. *Ind. Corp. Change* 28 (3), 477–501.
- Martens, B., Tolan, S., 2018. Will this time be different? A review of the literature on the Impact of Artificial Intelligence on Employment, Incomes and Growth JRC Digital Economy Working Paper 2018-08.
- Michaels, G., Natraj, A., Van Reenen, J., 2014. Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. *Rev. Econ. Stat.* 96 (1), 60–77.
- Reijnders, L.S., de Vries, G.J., 2018. Technology, offshoring and the rise of non-routine jobs. *J. Dev. Econ.* 135, 412–432.
- Ross, M.B., 2017. Routine-biased technical change: Panel evidence of task orientation and wage effects. *Labour Econ.* 48, 198–214.
- Stehrer, R., Bykova, A., Jäger, K., Reiter, O., Schwarzhappel, M., 2019. Industry level growth and productivity data with special focus on intangible assets. WIIW Report on Methodologies and Data Construction for the EU KLEMS Release 2019.
- Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., de Vries, G.J., 2015. An illustrated user guide to the world input–output database: the case of global automotive production. *Rev. Int. Econ.* 23 (3), 575–605.
- Van Reenen, J., 2011. Wage inequality, technology and trade: 21st century evidence. *Labour Econ.* 18 (6), 730–741.
- Yang, Z., 2017. Who Will Satisfy China's Thirst for Industrial Robots? *Diplomat*.